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Masterpiece Optimization Algorithm: A New Method for Solving Engineering Problems

Mohammad Reza Ghasemi [1,*]; Nader Haji Aghajanpour [2]; Hamed Ghohani Arab [3]

1. Professor, Department of Civil Engineering, University of Sistan and Baluchestan, Zahedan, Iran
2. Ph.D. Candidate, Department of Civil Engineering, University of Sistan and Baluchestan, Zahedan, Iran
3. Associate Professor, Department of Civil Engineering, University of Sistan and Baluchestan, Zahedan, Iran

* Corresponding author: *mrghasemi@eng.usb.ac.ir*

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ABSTRACT

The "Masterpiece Optimization Algorithm (MOA)" is introduced as a new nature-inspired meta-heuristic optimization method that mimics the masterpiece of Japanese Male Puffer Fishes (MPFs) that succeed in mating. Actually, the nest prepared by the MPFs for spawning is known as the masterpiece. Due to the importance of seabed fine sand to fish reproduction, the proposed algorithm is based on movement and accumulation of seabed fine sand particles. In order to find a place with a sufficient amount of fine sand for spawning, the MPF starts a search on the seabed. It then constructs the nest so that fine sand covers the eggs. The location with the greatest quantity of fine sand is where the majority of egg protection occurs. In the algorithm, this point is considered the global optimum. Now, to handle this content, in the first iteration of the proposed algorithm, different points in the answer zone are introduced for the MPF. Then, the MPF selects a point for the nest location using the Evaluator Function (EF). In continuation of the first iteration, three steps are executed. The point acquired in the third step represents a local optimum. For the next iteration, this point is deemed the nest location, and the aforementioned three steps are also executed. This process is done iteratively during each iteration. The best point of the last iteration is the global optimum of the problem in the answer zone. The obtained solutions of the MOA were then compared with some available techniques in the literature.

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1. Introduction

1.1. History of meta-heuristic optimization methods

Optimization is one of the universe's features. There is no doubt that it plays a key role in formation and stability of the universe. A little thinking about the phenomena of the universe reminds us that optimality is a fundamental principle of nature. For example, atoms form in a state where the energy of electrons is optimal [1]. Then, molecules and material crystals form in an optimal state of energy. This process, which makes it easy to adapt to the environment, is continued at higher levels. One of the most obvious behaviors observed in animals is to find food. There are many researchers who have started extensive studies in the field of optimization. Meta-heuristic optimization methods that have become famous in engineering in recent years are inspired by nature. The following four groups can be a suitable division for these methods: human-based, evolution-based, swarm-based, and physic-based algorithms.

The human-based algorithms mimic human behaviors and activities. The following are examples of human-based methods: Teaching-Learning Based Optimization (TLBO) [2], Harmony-Search (HS) [3], Taboo Search (TS) [4,5], Group Search Optimizer (GSO) [6], and War Strategy Optimization algorithm (WSO) [7].

In The evolution-based algorithms that are inspired by natural evolution rules, a random initial population is created and evolves in the next generation. The most famous evolution-based method is the Genetic Algorithm (GA) [8–10]. This method is based on Darwinian evolution theory. In addition, the following methods may be categorized in this group: Evolution Strategy (ES) [11], Genetic programming (GP) [12], Biogeography Based Optimizer (BBO) [13], and Population Based Incremental Learning (PBIL) [14].

In the swarm-based algorithms that are inspired by the social behavior of animal groups, the number of creatures moves in a search space to find the best solution. The most popular method of the swarm-based group is the Particle Swarm Optimization (PSO) [15]. In addition, the following methods can also fall into this group: Ant Colony Optimization method (ACO) [16], Bird Mating Optimizer (BMO) [17], Fruit-fly Optimization Algorithm (FOA) [18], Krill-Herd (KH) [19], Gannet Optimization Algorithm (GOA) [20], Artificial Rabbits Optimization (ARO) [21], Starling Murmuration Optimizer (SMO) [22], gaze cues learning-based grey wolf optimizer (GGWO) [23], GWOEHO [24], and artificial Jellyfish Search (JS) optimizer[25].

The physic-based algorithms mimic physic rules in the universe. The following methods are examples of this group: Simulated-Annealing (SA) [26], Gravitational Local Search Algorithm (GLSA) [27], Big-Bang, Big-Crunch (BB-BC) [28], Central Force Optimizer (CFO) [29], and Gravitational Search Algorithm (GSA) [30].

Some methods are introduced as a combination of two categories, such as: Sine-Cosine hybrid optimization algorithm with Modified Whale Optimization Algorithm (SCMWOA) [31], enhanced Quantum behaved Particle Swarm Optimization (e-QPSO) [32], and hybrid PSO-GRG [33]. In addition, Lamghari et al. (2022) proposed a new metaheuristic method. In this method, the components from exact algorithms are hybridized [34]. A hybrid Arithmetic Optimization

Algorithm (AOA) with Gold-SA was presented by Liu et al. (2022). This method, called HAGSA, improves the performance of AOA [35].

Some researchers improved the performance of the existing methods. A Balanced Teaching-Learning Based Optimization was presented by Taheri et al. (2021). This method, called BTLBO, improves the performance of TLBO [36]. The memory-based Grey Wolf Optimizer was proposed by Gupta and Deep (2020). This method, called mGWO, is a modification of Grey Wolf Optimizer (GWO) [37]. In another study, Dhawale et al. (2023) enhanced the Harris Hawk's Optimizer (HHO) in both exploration and exploitation phases [38].

The MOA that is presented in this article is placed in the swarm-based group.

1.2. Masterpiece of japanese MPF

Every creature struggling to survive may have its most important task in life. The latest research about the Japanese puffer fish shows optimal performance in reproductive behavior [39]. The MPF plays an essential role in reproduction, including determining the spawning location, building the nest, and providing coverage for the eggs until they hatch. Due to the seven to nine days of continuous nest construction and the nest's unique shape, it has been dubbed the masterpiece or mysterious circle. In the nest, the prepared spawning bed is composed of fine sand. On the other hand, the cover protecting the eggs is composed of fine sand, too. After the eggs are hatched, due to the reduction of fine sand, the MPF doesn't reuse a nest [39]. It seems the fine sand is necessary for the reproduction of Japanese puffer fishes, and the optimal performance is for the MPF to find a place with a sufficient amount of fine sand to construct the nest in. The female fish then enters the nest and spawns. The eggs that are well protected will then turn into fish. Thus, after spawning, there is a point with the maximum volume of fine sand to cover eggs. In the algorithm, this point is assumed the global optimum. The second section of the paper describes how to reach this point in an optimization problem by drawing inspiration from the masterpiece. An illustration of the seabed search and the masterpiece constructed by MPF is shown in Fig. 1.

(a) Fine sand exploration

(b) Masterpiece constructed by MPF (spawning nest)

Fig. 1. The role of the MPF in reproduction.

2. Masterpiece optimization algorithm

As stated earlier, the fine sand accumulated on the seabed is treasured for the fish because it ensures their regeneration and survival over time. The MOA described in this section tries to find the points on the seabed (response area) that have the maximum volume of fine sand with the help of spawning nest geometry as well as water flow. It is important to note that many MPFs attempt to mate, but only one is chosen by the female after examining their prepared nest. Therefore, the MPF may not be chosen and mated [39]. The proposed algorithm is written for an MPF that succeeds in reproduction.

Since many of the problems are constrained, use has been made of an Evaluator Function (*EF*) to evaluate the volume of the fine sand in the searching zone [40]. Thus, it gives:

$$EF = GF\left(1 \pm r_{p_i}.CV^{2}\right)$$
$$r_{p_i} = r_{p_{i-1}}\left(1.1^{\left[\frac{i}{10}\right]}\right) \tag{1}$$

Where, GF is the Goal Function, CV is the Constraint Violation, and r_{p_i} is the penalty coefficient for constraint violation in iteration *i*. It is based on statistical studies that cause a strong convergence. [] shows the integer part, and the plus and minus signs are used for the minimization and maximization, respectively.

In the beginning of the algorithm, some random search points are created in the response area. Then the volume of fine sand is checked in them using Eq. (1). The best point of these created points is the point with the minimum *EF* in minimization problems or the maximum *EF* in maximization problems. In the first iteration, the location of this best point is considered the center of the nest. In continuation of the first iteration and also in each iteration of the algorithm, the following three steps are executed:

2.1. Step 1: Choosing the best point inside the nest

Due to the circular shape of the puffer fish's masterpiece, the relations produced in two consecutive dimensions follow the equation of a circle. It means that the relations in the even dimension depend on the odd dimension. It should be noted that in the construction of the nest, the MPF accumulates fine sand in peripheral dents (valleys). After spawning, the sand accumulated in dents is moved by the water flow and covers the eggs [39]. Therefore, in the algorithm provided and developed, some points are created on the imaginary circle perimeter as the valleys. Also, some search points are created around the center of the nest inside the imaginary circle. The valleys are created using the following relations

$$x_{i_{new}}^{d=2m-1} = x_{i_{center}}^{d=2m-1} + r_i^{\,d} \times \cos(a) \tag{2}$$
$$x_{i_{new}}^{d=2m} = x_{i_{center}}^{d=2m} + r_i^{\,d} \times \sin(a) \tag{3}$$

Where, *2m-1* shows the odd direction and *2m* indicates the even direction. a is the angle of the intended valley. It alters from the [0,2π] interval as a division of the number of valleys. r_i^d is the radius of the nest reduced linearly in each iteration as follows:

$$r_0^d = 0.5\left(x_{max}^d - x_{min}^d\right) \tag{4}$$

$$\begin{cases} r_i^d = r_0^d - r_0^d \times \dfrac{i-1}{0.5\times i_{max}} & i \le 0.5\times i_{max} \\ r_i^d = r_0^d - r_0^d \times \dfrac{i-0.5\times i_{max}-1}{0.5\times i_{max}} & i > 0.5\times i_{max} \end{cases} \tag{5}$$

Where, x_{min}^d and x_{max}^d are, respectively, the minimum and maximum values extractable for the variables in direction *d*, r_0^d is the initial radius of the nest, r_i^d is the circle radius in iteration i, and i_{max} is the maximum number of iterations. Exploration and exploitation are two necessary operations that must be performed in order to improve the performance of meta-heuristic algorithms. As observed in Eq. (5), the radius of the nest reaches zero at the middle of the total iterations and increases in the next iteration. In fact, the exploration is performed in the first relation of Eq. (5), while the exploitation is performed in the second relation.

The number of search points within the nest in the MOA is a submultiple of four. Using four random numbers ($a1,a2,a3,a4$) from the interval [0, 1], the following relations produce these four points in the four quarters of the circle (see Fig. 2):

$$x_{i_{new\,1}}^{d=2m-1} = x_{i_{center}}^{d=2m-1} + a4\times(a1\times r),\quad x_{i_{new\,1}}^{d=2m} = x_{i_{center}}^{d=2m} + a4\times\sqrt{(r^2-(a1\times r)^2)} \tag{6}$$

$$x_{i_{new\,2}}^{d=2m-1} = x_{i_{center}}^{d=2m-1} + a3\times(a2\times r),\quad x_{i_{new\,2}}^{d=2m} = x_{i_{center}}^{d=2m} - a3\times\sqrt{(r^2-(a2\times r)^2)} \tag{7}$$

$$x_{i_{new\,3}}^{d=2m-1} = x_{i_{center}}^{d=2m-1} - a2\times(a3\times r),\quad x_{i_{new\,3}}^{d=2m} = x_{i_{center}}^{d=2m} + a2\times\sqrt{(r^2-(a3\times r)^2)} \tag{8}$$

$$x_{i_{new\,4}}^{d=2m-1} = x_{i_{center}}^{d=2m-1} - a1\times(a4\times r),\quad x_{i_{new\,4}}^{d=2m} = x_{i_{center}}^{d=2m} - a1\times\sqrt{(r^2-(a4\times r)^2)} \tag{9}$$

r equals r_i^d, which is calculated using equation (5). The volume of fine sand accumulated in valleys and search points is evaluated using *EF*.

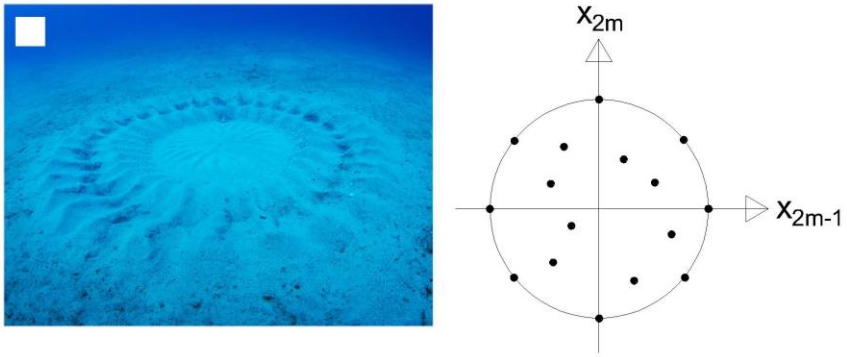

Fig. 2. Produce search points as the spawning nest in step 1.

2.2. Step 2: Calculating velocity and direction of water flow

As illustrated in Fig. 3, the water flow into the nest is radially directed. It means the water enters the nest through half of the valleys and leaves the nest through the other half of the valleys [39]. The fine sand on the seabed is moved by the water flow. Logically, the valleys in which the flow direction is output should have a higher volume of fine sand. So, the algorithm identifies fifty percent of adjacent valleys with the greatest volume of fine sand (minimum EF for minimization; see Fig. 4). The orientation of the outlet flow is then considered for these valleys.

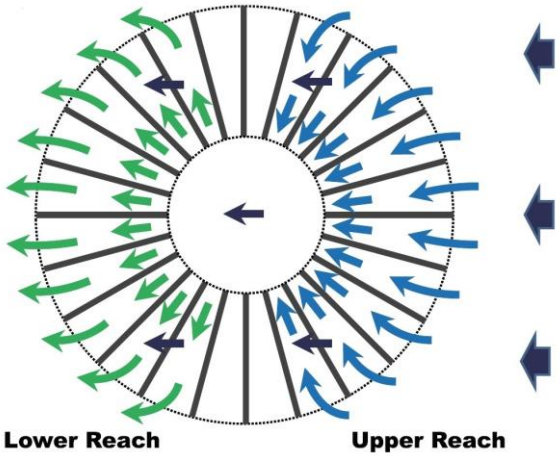

Fig. 3. Flow direction inside the nest.

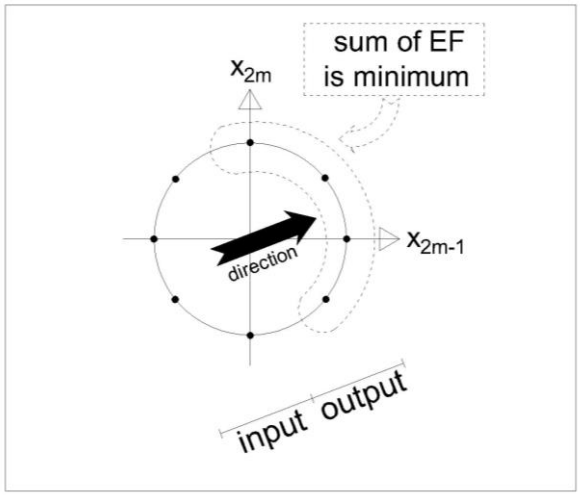

Fig. 4. Detecting flow direction inside the nest.

One of the factors that causes the sand movements in the seabed is water flow. Dyer (1980) has presented a relation to determine the velocity profile as follows [41]:

$$V = \frac{u^*}{K_s} ln(y_w / Z_0) \tag{10}$$

Where, u^* is the friction velocity, K_s is the bed shear constant, Z_0 is the bed roughness length, and y_w is the desired height.

As a logical assumption the u^* is considered 2 $\frac{cm}{s}$. According to the reference [41], the K_s is equal to 0.4. The seabed sediment is moved like a blanket [41]. Due to the nature of sand movement, the MOA considers the y_w equal to half of sand layer thickness. So, the y_w is assumed 20 cm. The Z_0 is considered 0.01 cm. Because, for a flat bed of a uniform grain size, the Z_0 is a thirtieth of the grain diameter [41]. Finally, the velocity profile is normalized by the problem and use as follows:

$$V^d \approx 0.033 \times \left(x^d_{max} - x^d_{min} \right) \tag{11}$$

Where, x^d_{max} and x^d_{min} are the maximum and minimum values that can be taken for x in direction d.

2.3. Step 3: Creating and checking new points in the flow direction

Four points with the highest density of fine sand are selected from the valleys and search points generated in the first step. Then, the average of x_i^d for the points on the circle perimeter that are in the outflow direction (Figure 4) is calculated for all problem dimensions (the number of problem variables). In order to generate new points in each dimension of the problem, we shift the selected point's coordinates by Δx^d toward the stated average. If the *EF* value of the new circumstance has improved, the coordinates of the point measured in that dimension will be replaced with new coordinates. This process is repeated for each dimension of the examined point, and a distinct point may be reported at the conclusion. During this process, a type of sensitivity analysis has been conducted, which greatly aids in determining the optimal answer. It is important to note that for each of the four points taken, a new point is created according to the number of the problem's dimensions. The following mathematical relationships describe how the aforementioned elements are formed:

$$\Delta x^d = V^d \times \Delta t \tag{12}$$

$$dir^d = sign(x^d_{i_{point}} - \overline{X}^d) \tag{13}$$

$$x^d_{i_{new}} = x^d_{i_{point}} + \Delta x^d . dir^d \tag{14}$$

Where, $x^d_{i_{point}}$ is the desired point's position in direction "*d*" and iteration "*i*", and $\overline{X}^d$ is the mean of x_i^d for the points on the circle perimeter that are in the outflow direction in dimension "*d*" of the problem. Δt is a random number between [0,p]. Fig. 5 explains how to construct points.

Before the next iteration is started, the nest's center is updated to the final point of the previous iteration. The new iteration begins with the assumption that the nest of the previous iteration is completely destroyed and the seabed is pristine. The iterations are continued until the convergence criterion is satisfied. Finally, the best point of the last iteration has been the best place on the seabed (the answer zone) for spawning. The best place for spawning mentioned above is the global optimum of the problem. Fig. 6 is shown the flowchart of the MOA.

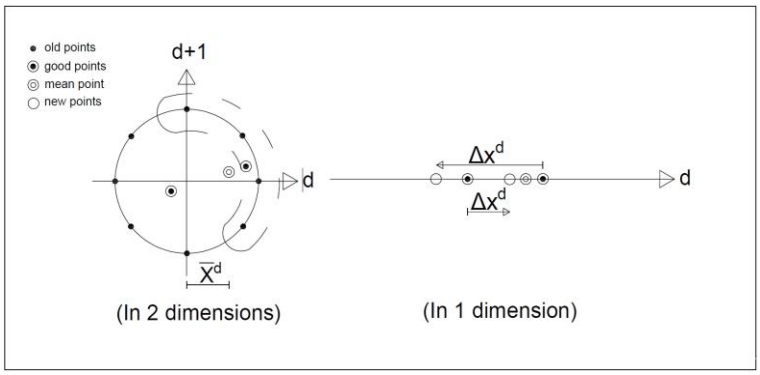

Fig. 5. Produce new points in step 3.

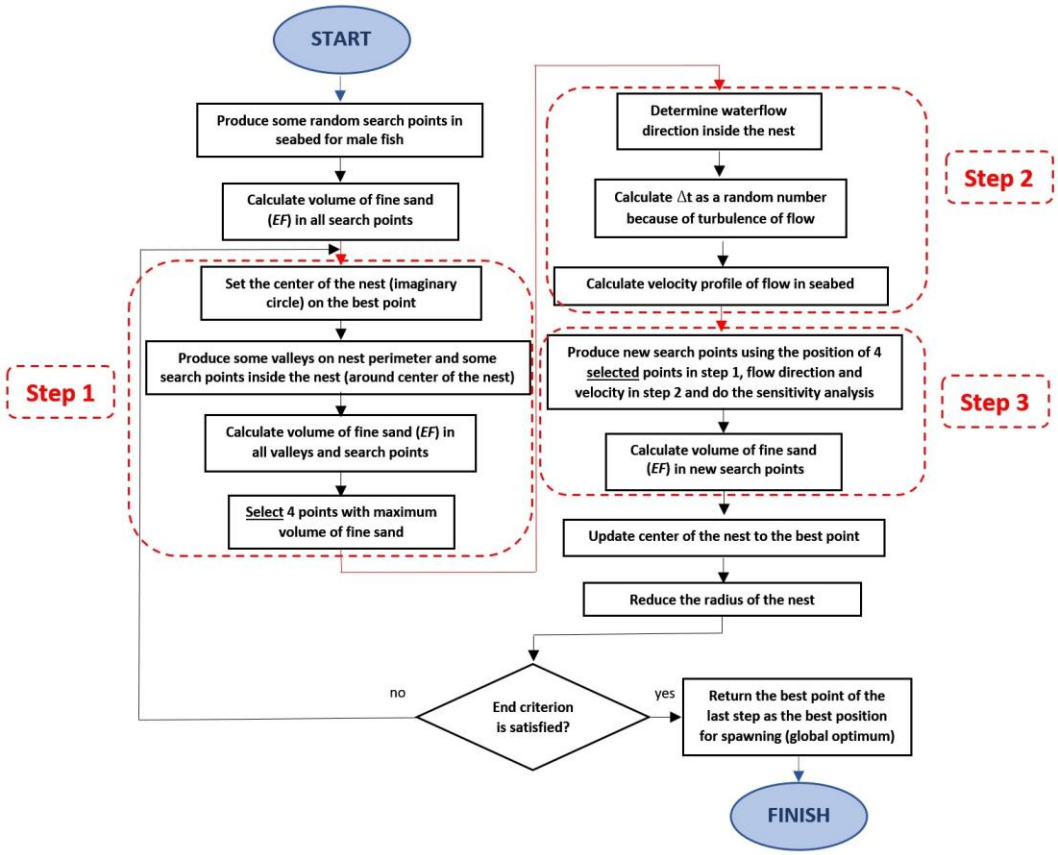
START
Produce some random search points in seabed for male fish
Calculate volume of fine sand (EF) in all search points
Set the center of the nest (imaginary circle) on the best point
Produce some valleys on nest perimeter and some search points inside the nest (around center of the nest)
Calculate volume of fine sand (EF) in all valleys and search points
Select 4 points with maximum volume of fine sand
Step 1
Determine waterflow direction inside the nest
Calculate Δt as a random number because of turbulence of flow
Calculate velocity profile of flow in seabed
Step 2
Produce new search points using the position of 4 selected points in step 1, flow direction and velocity in step 2 and do the sensitivity analysis
Calculate volume of fine sand (EF) in new search points
Step 3
Update center of the nest to the best point
Reduce the radius of the nest
End criterion is satisfied?
no
yes
Return the best point of the last step as the best position for spawning (global optimum)
FINISH

Fig. 6. Flowchart of the MOA.

3. Numerical result

In this section, three famous optimization problems are solved using MOA. In addition to the number of iterations that must be specified at the beginning of the solution, the algorithm will stop if there is not much change in the value of the *EF* in 10 consecutive iterations. The following relation is presented for the stop condition:

$$\frac{EF_{i-10} - EF_i}{EF_{i-10}} \times 100 \le 0.5 \quad , \quad i \ge 20 \tag{15}$$

Where, EF_i is the EF in iteration i. After 10 runs, the obtained results are compared with the available methods in the literature and presented in separate tables.

3.1. Mathematical benchmark problems

The solutions to the 14 Functions of CEC in reference [42] are attempted here by MOA. The 3D map for the 2D function of CEC functions is plotted in Fig. 7.

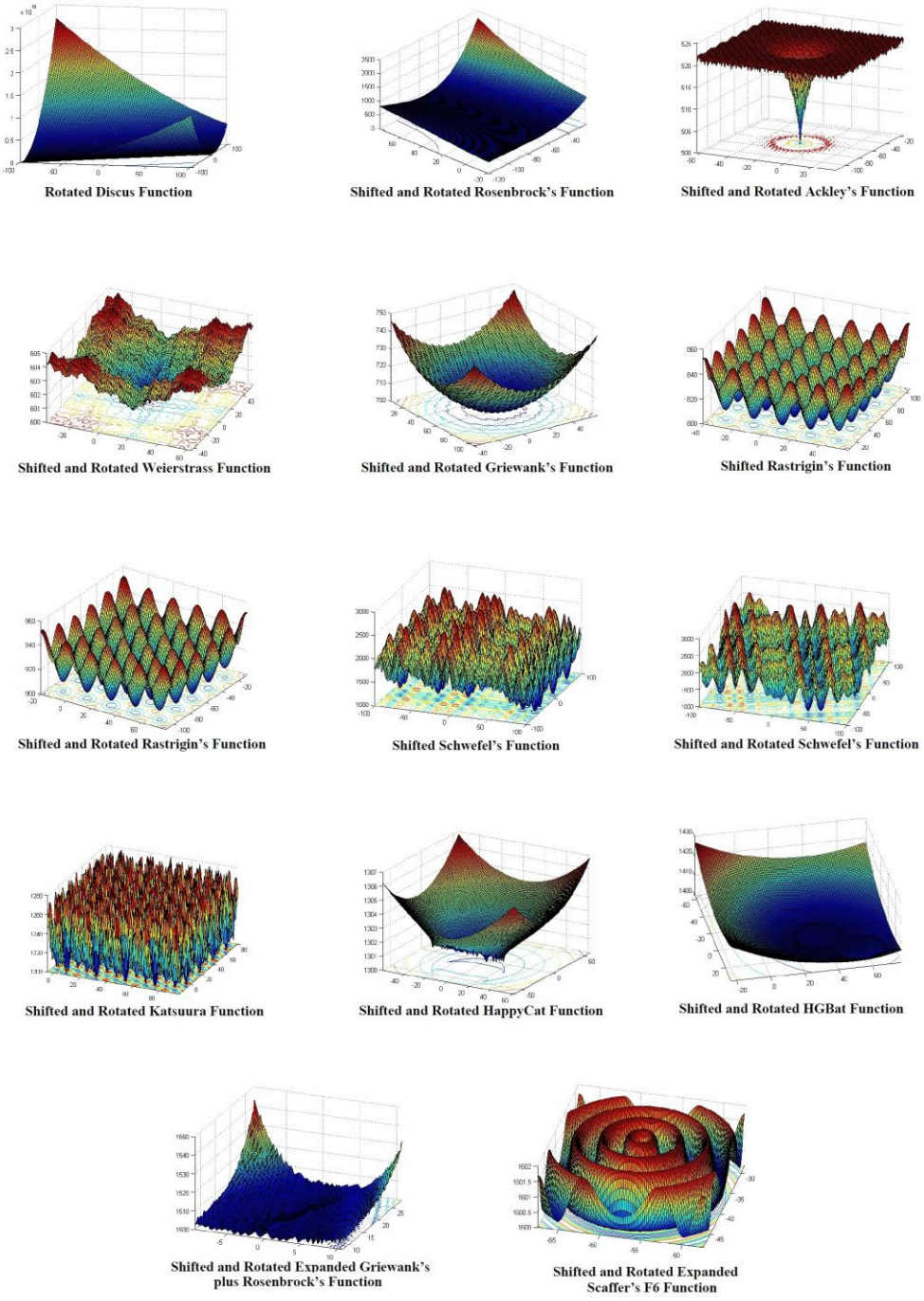
Rotated Discus Function
Shifted and Rotated Rosenbrock's Function
Shifted and Rotated Ackley's Function
Shifted and Rotated Weierstrass Function
Shifted and Rotated Griewank's Function
Shifted Rastrigin's Function
Shifted and Rotated Rastrigin's Function
Shifted Schwefel's Function
Shifted and Rotated Schwefel's Function
Shifted and Rotated Katsuura Function
Shifted and Rotated HappyCat Function
Shifted and Rotated HGBat Function
Shifted and Rotated Expanded Griewank's plus Rosenbrock's Function
Shifted and Rotated Expanded Scaffer's F6 Function

Fig. 7. The 3D map for the 2D CEC functions.

The CEC functions have already been attempted and solved by Yu et al. using FWA-DM [43]. The results of the MOA and the FWA-DM for the 10 and 30 dimension problems are presented in tables 1 and 2, respectively. To assess the mobility and reliability of the proposed algorithm, the program had to be run 50 times. Tables 1 and 2 show the MOA can reach acceptable answers. So, in the results, the efficiency of the presented method is evident. Here, r_{p_0} is adjusted to 5. There are 200 search points in the algorithm at start and also, 201 search points is assumed in the solving procedure. (1 in the center of the nest, 100 around the center, and 100 on the nest perimeter).

Table 1
CEC2014 - 10 Dimension results.

		Best	Worst	Average	Standard deviation	Median
Discus Function	MOA	0.0008	0.0764	0.0227	0.02702	0.0060
	FWA-DM	0.0009	5.94e-8	1.88e-9	9.02e-9	5.38e-18
Rosenbrock's Function	MOA	0.00072	4.7806	2.8335	1.3156	2.7803
	FWA-DM	0.0008	4.730	1.410	1.600	0.084
Ackley	MOA	20.0001	20.0001	20.0001	0.0000	20.0001
	FWA-DM	20.000	20.010	20.000	0.0417	20.000
Weierstrass	MOA	0.0064	1.2728	0.5396	0.3369	0.5396
	FWA-DM	0.0034	2.480	0.706	0.640	0.574
Griewank	MOA	0.0087	0.2035	0.0761	0.0236	0.0761
	FWA-DM	0.0172	0.224	0.0948	0.0492	0.0861
Shifted Rastrigin	MOA	0.0890	1.9899	0.9899	0.0402	0.9899
	FWA-DM	0.000	3.980	0.254	0.809	1.78e-15
Shifted and Rotated Rastrigin	MOA	1.9849	15.9193	6.0592	2.9368	5.4672
	FWA-DM	1.99	16.90	6.010	2.450	5.970
Shifted Schwefel	MOA	0.0871	7.9320	2.2200	2.9712	0.6362
	FWA-DM	9.09e-13	6.950	1.590	2.08	0.375
Shifted and Rotated Schwefel	MOA	22.3239	185.8577	86.2017	38.4674	81.2763
	FWA-DM	39.800	813.000	372.000	153.000	360.000
Shifted and Rotated Katsuura	MOA	0.0355	0.0461	0.0408	0.0075	0.0408
	FWA-DM	3.34e-6	0.284	0.043	0.0478	0.0282
HappyCat	MOA	0.0199	0.0619	0.0609	0.0015	0.0609
	FWA-DM	0.034	0.299	0.121	0.0718	0.104
HGBat	MOA	0.0214	0.0217	0.0216	0.0002	0.0216
	FWA-DM	0.039	0.552	0.214	0.120	0.186
Griewank + Rosenbrock	MOA	0.1520	0.9410	0.5470	0.5585	0.5470
	FWA-DM	0.321	1.470	0.775	0.263	0.743
Shifted and Rotated Expanded Scaffer's F6	MOA	0.6243	2.0093	0.9495	0.4700	0.9705
	FWA-DM	0.796	2.82	1.760	0.468	1.730

Table 2
CEC2014 - 30 Dimension results.

		best	worst	average	standard deviation	median
Discus Function	MOA	0.0008	0.0955	0.0226	0.0010	0.0114
	FWA-DM	2.35e-17	2.23e-15	4.42e-16	4.74e-16	2.48e-16
Rosenbrock's Function	MOA	0.0099	43.9844	8.1410	5.9840	9.4008
	FWA-DM	0.0012	74.400	20.400	19.100	15.800
Ackley	MOA	20.0000	20.1017	20.0161	0.0272	20.0002
	FWA-DM	20.400	20.600	20.500	0.0536	20.500
Weierstrass	MOA	0.0842	19.1568	8.8030	3.3227	8.7647
	FWA-DM	0.0812	20.900	12.900	8.250	17.500
Griewank	MOA	0.0001	0.0265	0.0061	0.0044	0.0062
	FWA-DM	0.000	0.0369	0.0086	0.0098	0.0074
Shifted Rastrigin	MOA	0.0000	0.0899	0.0388	0.0040	0.0310
	FWA-DM	0.000	2.69e-12	1.13e-13	4.51e-13	1.78e-15
Shifted and Rotated Rastrigin	MOA	31.8387	57.4553	40.1121	7.1157	40.6520
	FWA-DM	33.200	78.200	56.600	10.800	56.200
Shifted Schwefel	MOA	2.2933	16.3716	4.6237	1.4665	4.9200
	FWA-DM	4.650	15.400	8.530	2.420	8.090
Shifted and Rotated Schwefel	MOA	132.2288	545.2928	93.8210	87.5645	91.6793
	FWA-DM	2000.000	3030.000	2630.000	248.000	2650.000
Shifted and Rotated Katsuura	MOA	0.0150	0.2877	0.0894	0.0570	0.0726
	FWA-DM	0.208	0.521	0.371	0.0666	0.370
HappyCat	MOA	0.1291	0.3636	0.2499	0.0572	0.2633
	FWA-DM	0.288	0.490	0.389	0.0551	0.400
HGBat	MOA	0.0967	0.2802	0.1919	0.0419	0.1947
	FWA-DM	0.178	0.740	0.269	0.0776	0.259
Griewank + Rosenbrock	MOA	2.6004	8.9873	4.9918	1.4635	4.9010
	FWA-DM	5.640	9.050	7.370	0.846	7.330
Shifted and Rotated Expanded Scaffer's F6	MOA	10.0825	10.9790	10.4483	0.5238	10.4677
	FWA-DM	10.300	11.400	11.000	0.271	11.000

The convergence history for the CEC functions attempted by MOA is presented in Fig. 8.

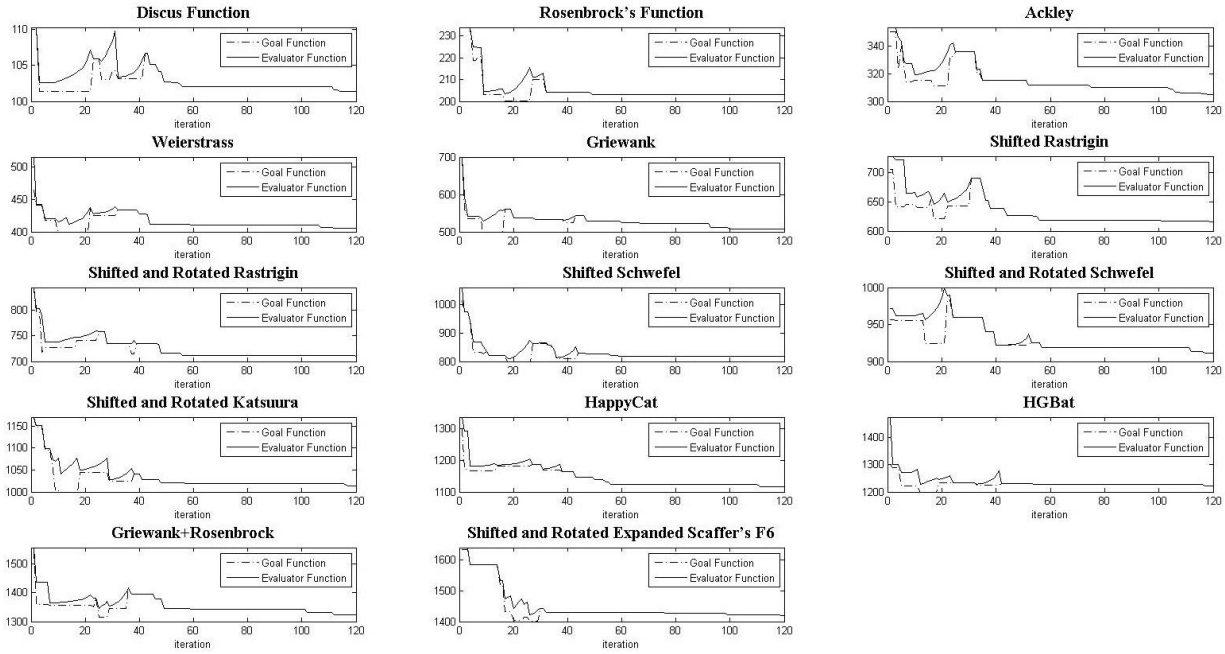

Fig. 8. The convergence history for the CEC functions.

3.2. Structural benchmark problem

The 25-bar truss is a popular engineering problem. This problem's primary objective is to reduce the truss's weight, which can be computed as follows:

$$W = \sum_{m=1}^{n} \gamma_m A_m L_m \tag{16}$$

Where, γ is the density of materials, A is the cross-sectional area of each bar element, L is the truss bar length, m is the counter of the truss members, and n is the total number of members in the truss.

In this problem, the density of materials is set to 0.1 $\frac{lb}{in^3}$ (2768 $\frac{kg}{m^3}$) and the elasticity modulus is 10 msi (68.95 GPa). The node displacements are limited to ±0.35 in (±0.889 Cm). Eight group divisions are considered for the members. The maximum and minimum values for allowable stresses for each group are expressed in Table 3. The load conditions that must be applied to the structure are shown in Table 4. The maximum and minimum cross-sectional areas of the members are 4 in^2 and 0.01 in^2, respectively. Fig. 9 shows the geometry of the problem.

Table 3
member stress limitations - 25-bar truss (*ksi*).

member number	compression limit	tension limit
1	35.092	40.000
2-5	11.59	40.000
6-9	17.305	40.000
10-11	35.092	40.000
12-13	35.092	40.000
14-17	6.759	40.000
18-21	6.959	40.000
22-25	11.082	40.000

Table 4
load conditions – 25-bar truss (*kips*).

		Direction		
load case	node	x	y	Z
1	1	1.0	10.0	-5.0
	2	0.0	10.0	-5.0
	3	0.5	0.0	0.0
2	5	0.0	20.0	-5.0
	6	0.0	-20.0	-5.0

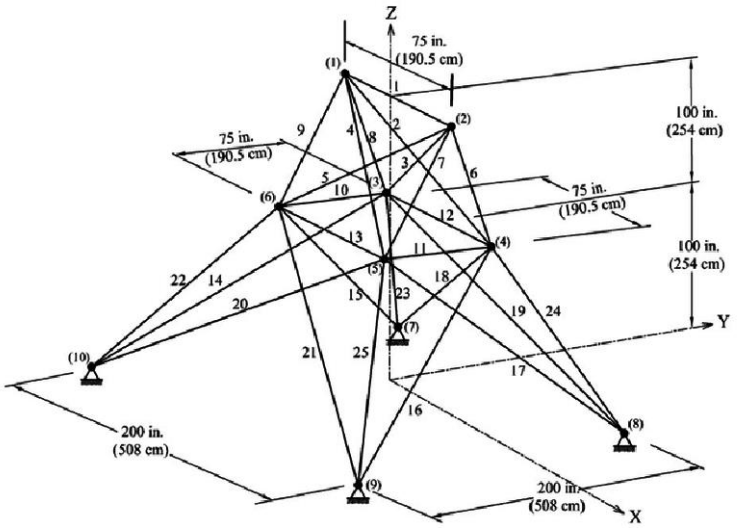

Fig. 9. Geometry of the 25-bar truss.

The 25-bar truss problem has already been attempted and solved by many researchers, such as Lee and Geem using HS [3], Sonmez using ABC [44], Kaveh et al. using CSP [45], and Varaee and Ghasemi using IGMM [46]. The obtained results by the MOA here are compared with those results and are expressed in Table 5, which shows the superiority of the MOA. The convergence history of the proposed method is presented in Fig. 10. Here, r_{P_0} is adjusted to 1.1. There are 40 search points in the algorithm at start and also, 9 search points is assumed in the solving procedure. (1 in the center of the nest, 4 around the center, and 4 on the nest perimeter).

Table 5
comparing results for 25-bar truss.

member number	HS	ABC	CSP	IGMM	present work
1	0.047	0.011	0.01	0.01	0.0122
2-5	2.022	1.979	1.91	2.006	1.8514
6-9	2.95	3.003	2.798	2.961	3.0353
10-11	0.01	0.01	0.01	0.01	0.0100
12-13	0.014	0.01	0.01	0.01	0.0100
14-17	0.688	0.69	0.708	0.687	0.6762
18-21	1.657	1.679	1.836	1.676	1.7607
22-25	2.663	2.652	2.645	2.668	2.6410
weight(lb)	544.38	545.19	545.09	545.19	545.12
NFEs	15,000	300,000	17,500	5,240	4000
C.V.	0.0715	0.058	0.0202	0	0

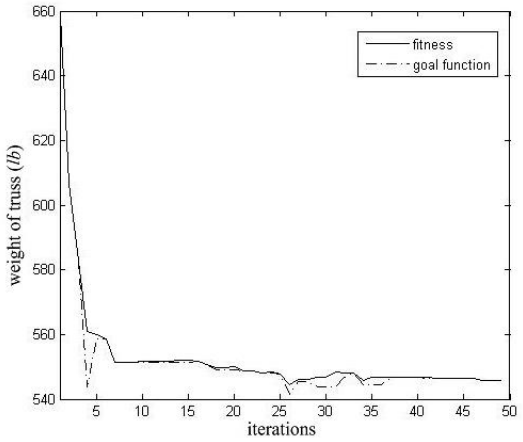

Fig. 10. Convergence history of 25-bar truss.

In order to better comprehend the enhancement of results obtained by the MOA, Reducing the number of function evaluations and the constraint violations are plotted in Fig. 11.

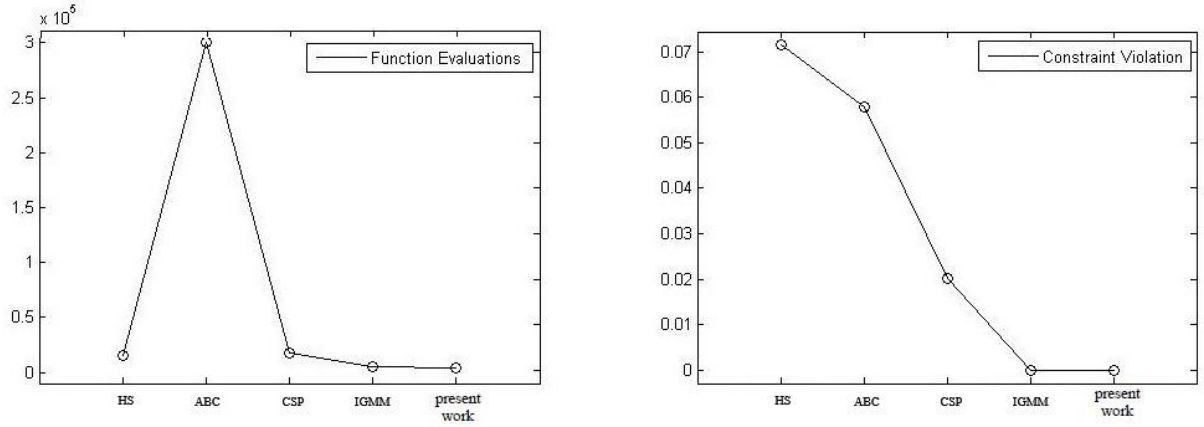

Fig. 11. (a) Comparing results for NFEs.- 25-bar truss; **(b)** Comparing results for C.V.- 25-bar truss.

3.3. Mechanical benchmark problem

The welded beam optimum design that is introduced by Rao [47] is one of the most challenging constrained problems in engineering. In this problem, the purpose is to reduce the construction cost considering the stress and strain constraints. Fig. 12 shows the geometry of the problem. The design variables are the weld's thickness ($h=x_1$), the welded joint's length ($l=x_2$), the beam's width ($d=x_3$), and the beam's thickness ($b=x_4$). The goal function and the constraints are as follows:

$$minf\ (\mathbf{X}) = 1.10471 x_1^2 x_2 + 0.04811 x_3 x_4 (14 + x_2) \tag{17}$$

$$g_1(\mathbf{X}) = \sqrt{\alpha^2 + \frac{\alpha\beta x_2}{D} + \beta^2} - 13600 \le 0 \tag{18}$$

$$g_2(\mathbf{X}) = \frac{504000}{x_4 x_3^2} - 30000 \le 0 \tag{19}$$

$$g_3(\mathbf{X}) = x_1 - x_4 \le 0 \tag{20}$$

$$g_4(\mathbf{X}) = 0.10471 x_1^2 + 0.04811 x_3 x_4 (14 + x_2) - 5 \le 0 \tag{21}$$

$$g_5(\mathbf{X}) = 0.125 - x_1 \le 0 \tag{22}$$

$$g_6(\mathbf{X}) = \frac{65856}{30000 x_4 x_3^3} - 0.25 \le 0 \tag{23}$$

$$g_7(\mathbf{X}) = 6000 - 0.61423 \times 10^6 \frac{x_3 x_4^3}{6} \left(1 - \frac{x_3 \sqrt{\frac{30}{48}}}{28} \right) \le 0 \tag{24}$$

$$Q = 6000 \left(14 + \frac{x_2}{2} \right) \tag{25}$$

$$D = \frac{1}{2} \sqrt{x_2^2 + (x_1 + x_3)^2} \tag{26}$$

$$J = \sqrt{2} x_1 x_2 \left[\frac{x_2^2}{6} + \frac{(x_1 + x_3)^2}{2} \right] \tag{27}$$

$$\alpha = \frac{6000}{\sqrt{2} x_1 x_2} \tag{28}$$

$$\beta = \frac{QD}{J} \tag{29}$$

$$0 \le x_1, x_4 \le 2 \quad , 0 \le x_2, x_3 \le 10 \tag{30}$$

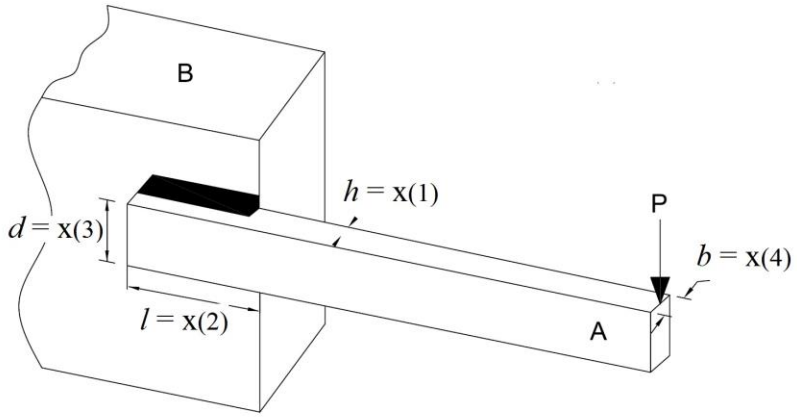

Fig. 12. Geometry of welded beam.

The welded beam optimum design has been solved before by Montes and Coello using GA [48], He and Wang using CPSO [49], Mirjalili et al. using MVO [50], Kaveh and Talatahari using ACO [51], and El-Kenawy et al. using SCMWOA [52]. The mentioned problem has been solved using the proposed method, and the obtained results are presented in Table 6 and compared with other research. Improvements in the responses of the proposed method are clearly visible. The convergence history of the proposed method is presented in Fig. 13. Here, r_{p_0} is adjusted to 1.1. There are 60 search points in the algorithm at start and also, 81 search points is assumed in the solving procedure. (1 in the center of the nest, 40 around the center, and 40 on the nest perimeter).

Table 6
the welded beam - comparing results.

	GA	CPSO	MVO	ACO	SCMWOA	present work
x_1	0.205986	0.202369	0.205463	0.2057	0.205604	0.20571
x_2	3.471328	3.544214	3.473193	3.471131	3.479712	3.4709
x_3	9.020224	9.04821	9.044502	9.036683	9.041001	9.0367
x_4	0.20648	0.205723	0.205695	0.205731	0.205739	0.20573
g_1	-0.103	-13.6555	0.0261	-0.0846	-25.5857	-0.0559
g_2	-0.2317	-75.8141	-47.1961	-0.5907	-30.4048	-0.5577
g_3	-0.0005	-0.0034	-0.0002	-3.10E-05	-0.0001	-2.00E-05
g_4	-3.43	-3.4246	-3.4317	-3.4329	-3.4313	-3.4329
g_5	-0.081	-0.0774	-0.0805	-0.0807	-0.0806	-0.0807
g_6	-0.2355	-0.2356	-0.2356	-0.2355	-0.2356	-0.2355
g_7	-58.6006	-4.427	-0.3596	-0.099	-2.6836	-0.0189
$f_{\min}$	1.728223	1.731484	1.725898	1.724912	1.726738	1.724892
NFEs	80000	30000	15000	17600	9900	9360

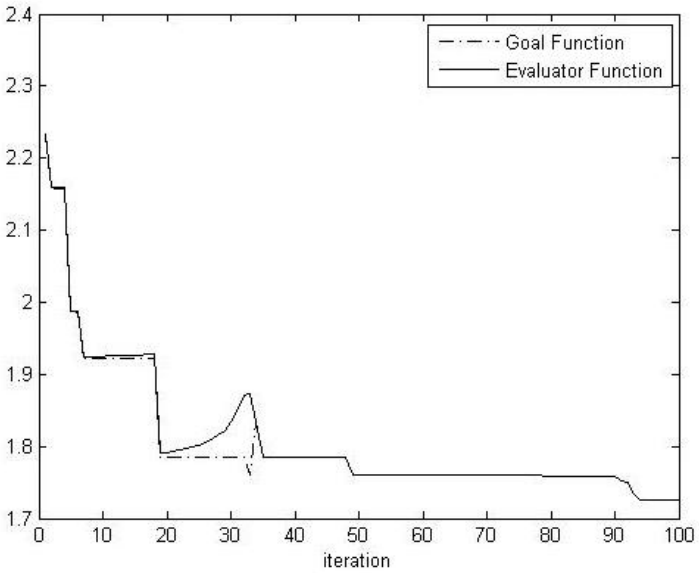

Fig. 13. Convergence history of welded beam.

In order to better comprehend the enhancement of results obtained by the MOA, Reducing the number of function evaluations is plotted in Fig. 14.

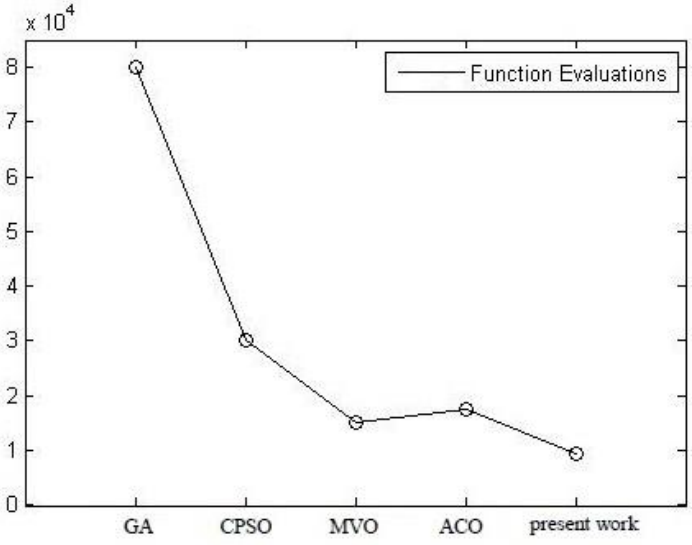

Fig. 14. Comparing results for NFEs. - welded beam.

4. Conclusion

In this paper, a new meta-heuristic, nature-inspired method is introduced. The proposed MOA is inspired by the masterpiece of Japanese puffer fish. In fact, the masterpiece is the nest that is constructed by MPF for spawning, a name given due to the high construction time and unique design of the nest. In the reproduction of pufferfish, the volume of fine sand on the seabed plays a key role. So, this method is focused on the volume of fine sand and its movement due to water flow on the seabed. The point with the maximum volume of fine sand in the MPF activity area

(answer zone) is the best point for spawning. The MOA tries to find this key point in the answer zone and reports it as the global optimum of the problem.

Each optimization method should find the optimal points through exploration and exploitation operations. In the MOA, these operations operate perfectly. To prove this claim, the proposed algorithm must reach accurate answers with a lower number of function evaluations. Also, the algorithm must not trap at the local optimal point. So, the efficiency of the proposed method was assessed through different benchmark problems when compared with available methods in the literature. The following results can be concluded:

1. The MOA achieves more accurate answers.
2. The MOA reaches the answers with a lower number of function evaluations.
3. In constrained problems, the constraint violation was equal to zero.
4. The MOA was able to achieve acceptable answers for mathematical problems.
5. The MOA increases the convergence speed while reducing analysis time due to the reduced number of function evaluations.
6. The MOA causes economic savings due to reduced analysis time.

Due to the high efficiency of the MOA, using this method is recommended for solving engineering constrained and unconstrained optimization problems.

Authors' contributions statement

N.H.A. proposed the idea, designed the research, did model analysis, data fitting, and made all figures and analyzed the results. M.R.G. and H.G.A. supervised the manuscript.

Competing interests

The authors declare no competing interests.

Data availability

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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